

Improved Process Control Through Real-Time Measurement of Mineral Content

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ABSTRACT

In a highly collaborative research and development project with mining and university partners, sensors and data-analysis tools are being developed for rock-mass characterization and real-time measurement of mineral content. Determining mineralogy prior to mucking in an open-pit mine is important for routing the material to the appropriate processing stream. A possible alternative to lab assay of dust and cuttings obtained from drill holes is continuous on-line sampling and real-time x-ray fluorescence (XRF) spectroscopy. Results presented demonstrate that statistical analyses combined with XRF data can be employed to identify minerals and, possibly, different rock types. The objective is to create a detailed three-dimensional mineralogical map in real time that would improve downstream process efficiency.

INTRODUCTION

The work described here is part of a collaborative research and development project funded by the Department of Energy's Office of Industrial Technologies. The overall objective of the work is to provide measurements while drilling to provide borehole profiles of mineral content and rock/fracture-characterization data that can be used to develop blast-design tools to achieve optimal fragmentation of rock. Partners on the project are the Lawrence Berkeley National Laboratory; the University of Arizona; Phelps Dodge Morenci, Inc.; Aquila Mining Systems LTD; and Split Engineering, LLC. Papers describing this work include D. Hopkins et al. (2000) and J. Kemeny et al. (2001).

The results described herein are from that part of the project focused on design and implementation of a prototype system to collect dust and cuttings during drilling, and analyze the samples collected to determine mineral content. The objective is to generate a three-dimensional map of mineralogy throughout the bench during drilling. Work is also underway to determine if the elemental-composition data being collected can also be analyzed to provide information about rock properties such as hardness that would be useful to blasting engineers.

X-ray fluorescence (XRF) spectroscopy is routinely used to analyze atomic composition in a wide range of applications including detection of environmental contamination in soils, rare-metal detection, and materials evaluation. The research challenges of adapting the technology for use as a field measurement tool include ensuring reliable and accurate measurements under field conditions, creating a robust system that can survive the harsh mining environment with minimal maintenance, and minimizing interference with drilling operations.

XRF SPECTROSCOPY

X-ray fluorescence (XRF) spectroscopy is a nondestructive technique for analyzing the elemental composition of solids and liquids. Measurements are made by irradiating a sample with high-energy photons, such as X-rays or gamma rays, and measuring the resulting radiation emitted by the material (see R. Giauque, 1994). When high-energy photons strike the sample, energy absorbed causes electrons to be ejected out of their shells to a higher orbit. This process, called the photoelectric effect, causes an unstable atomic condition. Electrons in outer shells drop down to fill the vacancies left by the ejected electrons; since outer-shell electrons have more energy than those in inner shells, the electrons moving into the inner shell have excess energy that is released as X-ray photons (see Figure 1). The irradiated surface emits a spectrum of scattered radiation and fluorescent x-rays. Each element has a unique X-ray signature that can be identified, and the number of X-rays of each type emitted by the sample is used to determine the concentration of each element.

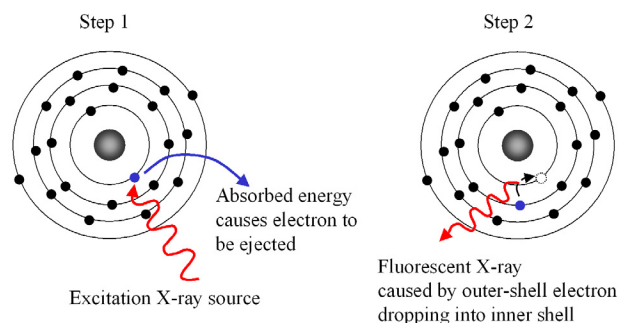


Figure 1. High-energy photons striking the sample cause inner-orbital electrons to be ejected from their shells. Fluorescence occurs when an outer-orbital electron drops down to fill the vacancy left by the ejected electron, causing an X-ray photon to be emitted. Each element has a unique X-ray signature.

Because of the well-defined energy signature of each element, it is possible to determine the elemental composition of a sample with very high precision. Detection resolution depends on the source, but is on the order of 1 to 25 parts per million (ppm). Accuracy improves with increasing time of exposure; measurement times are on the order of seconds to a few minutes. Accuracy also depends on the atomic number of the element being measured; elements with high atomic numbers are easier to measure than those with low numbers. This arises from what is called Auger electron emission, which occurs when fluorescence radiation excites an electron from an outer shell rather than being emitted from the atom. Auger electron emission declines with increasing atomic number. Sample penetration by source X-rays and fluorescence energy are also greater for higher order elements.

Commercially available XRF spectrometers generally consist of a source of excitation, a radiation detector, and a display of the spectral response of the sample. Excitation sources are either X-ray tubes, or sealed sources of a radioactive material. For field use, X-ray sources are probably not practical because of their size and power requirements. However, compared to radioactive sources, X-ray tubes have the advantage of operating on demand. Devices that use radioactive sources are better suited to field applications because they are lightweight (typically 1-2 pounds), they can run off batteries, and they can be easily housed in a small portable unit. However, radioactive sources must be replaced periodically, on the order of once per year. Radiation detectors are made from a variety of semiconductor materials, which differ with respect to resolution, maintenance requirements, cost, operating conditions, and range of detection. The best radiation source and detector for the test site are under investigation.

MINERALOGY OF THE MINE

The results presented below are based on analysis of field samples collected at the Phelps Dodge Morenci Mine in southeastern Arizona. The Morenci mining district is the largest producing porphyry-copper deposit in North America. The porphyry-copper deposits in this district are associated with granitic rock composed of large crystals in a fine-grained matrix; for detailed description of the geology in this region see the volume edited by S. R. Titley and C. L. Hicks (1971). The geology is similar to that of other large copper deposits in volcanic arcs associated with subduction zones. Economically important minerals in these deposits generally occur as small grains that are either dispersed throughout the rock, or concentrated along closely spaced fractures; these deposits are typically found in and around porphyritic felsic plutons that are within a few kilometers of the earth's surface.

The Precambrian rocks consist of schist, quartzite, granite, and granodiorite (see R. T. Moolick and J. J. Durek, 1971). The basement rock is overlain by about 300 meters (1000 ft) of Paleozoic sedimentary deposits consisting of quartzite, limestone, and shale. These sedimentary rocks are, in turn, overlain by remnants of Cretaceous shale and sandstone that are as much as 250 meters (840 ft) thick. Tertiary volcanic flows and intrusive pipes of basalt, andesite and rhyolite encircle the district.

It does not appear that there was any igneous activity in the region between the Precambrian period and the Laramide intrusion that occurred during the Cretaceous-Tertiary period. The stocks or laccoliths and associated dikes and sills created at that time are almost entirely porphyritic in texture, and developed during three distinct stages. The rock types corresponding to these stages are

described below, as paraphrased from R. T. Moolick and J. J. Durek (1971):

Diorite Porphyry: The southwestern part of the intrusive complex is a gray mottled diorite porphyry containing large phenocrysts of hornblende and labradorite.

Quartz monzonite porphyry: The monzonite porphyry intrusive has the greatest exposed area and is the principal ore bearing rock. It consists of small, closely-packed phenocrysts of orthoclase, albite, and oligoclase in a microcrystalline groundmass of quartz and feldspar. Small quartz phenocrysts are present only locally, and quartz is generally confined to the groundmass. Biotite appears to have been abundant but rarely preserved. When only weakly altered, the rock is gray, brownish gray or greenish gray; it is generally strongly altered and light gray or white.

Granite porphyry: Much of the central part of the intrusive complex consists of granite porphyry containing medium to large well-spaced phenocrysts of orthoclase, albite and quartz. Several ages of granite porphyry occur and have intrusive contacts and marked textural differences. The youngest granite porphyry contains euhedral quartz phenocrysts as much as 4 cm in diameter and is weakly mineralized. The older granite porphyry usually contains smaller quartz phenocrysts and more closely spaced feldspar phenocrysts. The rocks in the Morenci district are almost entirely similar to those described during the three stages, the rock types corresponding to these stages are diorite porphyry, quartz monzonite porphyry, and granite porphyry. The rocks pictured indicate the tremendous variety in

the main ore body in the Morenci district encompasses about two-thirds of the quartz monzonite porphyry intrusion. Moolick and Durek report that intense fracturing in the intrusive complex is characteristic of this zone.

Alteration

As explained by S. C. Creasey (1971), porphyry intrusion of a mixed sedimentary sequence was followed by extensive alteration of the wall rocks and porphyry. Creasey writes that it is difficult to distinguish between the metamorphic contact and the hydrothermal alteration. There are three primary zones where alteration silicates and carbonates are observed:

- Propylitic Zone, with chlorite, epidote, calcite, talc, green biotite, biotite, hornblende, and sericite.
- Argillic Zone, with quartz, sericite, kaolinite, montmorillonite, chlorite, and pyrite, and
- Phyllic Zone, with quartz-sericite and pyrite.

Ore-bearing minerals are found in all of these alteration zones, as well as in the host rock. The primary ore-

Figure 3. A rock sample from the older-granite-porphyry zone. Alteration is quartz-sericite. Copper oxide is present in the sample as chrysocolla. The copper concentration measured using XRF analysis is 8360 ppm or 0.83% for this sample.

bearing minerals are chalcocite, covellite, cuprite, chalcocopyrite, pyrite, cuprite, malachite, azurite, chrysocolla, brochantite, native copper, molybdenite, and sphalerite. The samples analyzed to date by XRF spectroscopy include most of these ore-bearing minerals, and include specimens from the three types of porphyry rock described above, as well as each of the three alteration zones, also described above. Typical rock samples from the field site are shown in Figures 2 and 3.

XRF ANALYSIS OF FIELD SAMPLES

Samples obtained in the field are evaluated using a bench-top XRF system. Calibration samples obtained from the National Institute of Standards and Technology (NIST) are also being evaluated. A preliminary series of laboratory measurements were conducted to demonstrate the ability of XRF spectroscopy to discern various minerals in samples collected in the field. A wide variety of rock samples and drill cuttings from boreholes were collected from the Phelps Dodge Morenci open-pit mine in Arizona. Seventy samples were prepared for XRF analysis; to obtain the best results possible, the samples were ground to powder. An example of the results obtained is shown in Figure 3. The elements in the gray-scale graph are arranged in order of atomic number, and indicate the concentration of each element in the sample normalized by the maximum measured concentration of that element across all 70 samples. Light colors indicate a relatively high concentration of a particular element (white corresponds to 100% of the maximum value), compared to dark shades, which indicate a relatively low concentration (black corresponds to 0%). For example, white indicates that the sample contains the highest measured concentration of that element among the 70 samples tested. Results of XRF analysis of samples collected during drilling are described below in the section summarizing field-test results.

PROTOTYPE ONLINE SAMPLE COLLECTION SYSTEM

During drilling, large amounts of dust are produced and flushed out of the borehole with compressed air. XRF spectroscopy requires only very small quantities of material for analysis. To obtain representative borehole samples during drilling, a prototype dust-collection system was designed and fabricated. The harsh mining environment and vibration of the drill rig require that the system be robust and simple, making it desirable to have as few moving parts as possible. It is also essential that the collection system not interfere with the drilling process, and not require special handling when the drill is moving between locations.

A cyclone was chosen to separate the dust from the transport medium, which can be air or a liquid. The sys-

tem built and tested for the current project uses air. The dust-laden air enters at the top of the cyclone in a tangential port (see Figure 4a). Centrifugal force causes the dust to be thrown against the cyclone walls; from there it spirals downward due to gravity. In the cone, the airflow velocity increases from top to bottom, until the vortex inverts, causing the air to flow upward in the center. The dust drops out at the bottom and clean air exits at the top, through the exhaust port. Recovery of up to 99% of the solid material is possible.

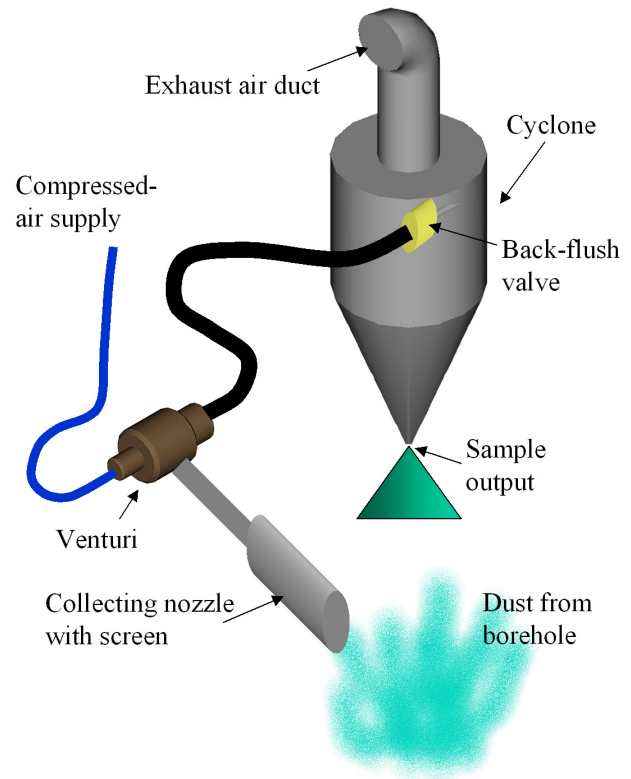


Figure 4a. Schematic view of the online dust/cutting collection system. During drilling, dust and cuttings are collected through a nozzle placed near the borehole. A venturi-suction system using compressed air supplied from the drill rig provides a continuous sampling of material during drilling; exhaust from the venturi system is routed to the cyclone where the solid material is separated from the air. Samples are collected at the bottom of the cyclone.

The cyclone operates without any moving parts, and does not contain filters or any other consumables that need to be replaced. The dust was collected through a nozzle equipped with a screen to prevent large debris from clogging the flexible hoses and pipes. Samples were also successfully collected without the nozzle; dust was collected directly from the hose placed near the borehole. A venturi-suction system was operated with compressed air from the drill rig. The exhaust from the venturi nozzle is routed to the cyclone for dust separation. Supplying compressed air is not a problem; drill rigs have large air compressors used to supply air that is used for cooling as

well as flushing cuttings out of the borehole. A picture showing the prototype collection system mounted on a drill rig is shown in Figure 4b.

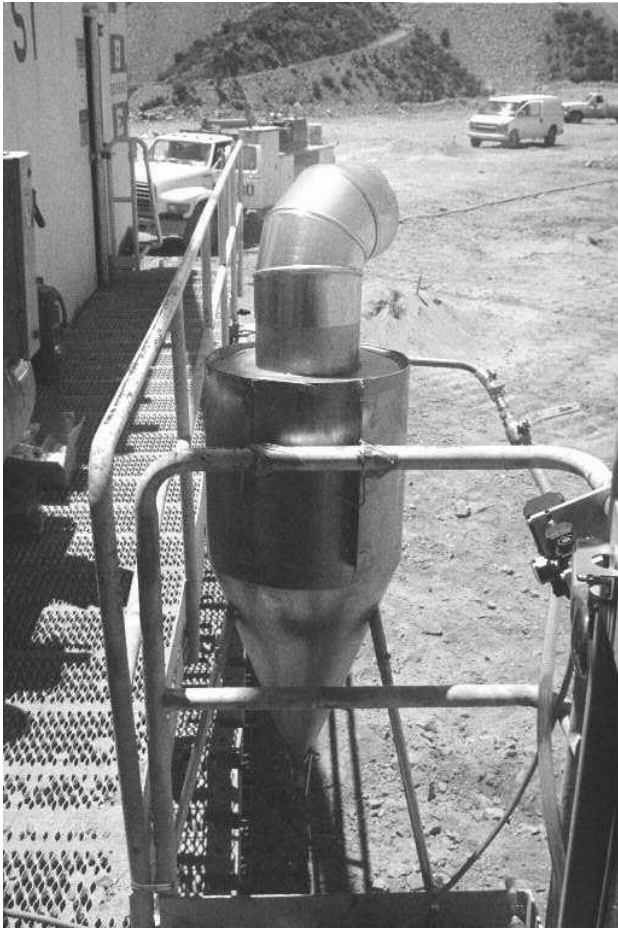


Figure 4b. Dust/cutting collection system installed on a drill rig.

FIELD TEST RESULTS

More than 90 dust/cutting samples were collected during a field experiment conducted at the Phelps Dodge Morenci Mine. The samples were collected during drilling, using the dust collection system described in the previous section. After initial difficulty in finding a good location for the collecting nozzle, it was placed next to the borehole exhaust system where a steady stream of dust and cuttings were retrieved. Samples were collected continuously over the entire drilling length of 18 meters (60 ft). Every 1.5 to 3.0 meters (5 to 10 ft) the sample jar was manually replaced; thus, each sample represents an average over the sample length. A next step in moving toward a stand-alone field system is automating the sample collection. The system could include an XRF analysis capability, or the samples could be logged and analyzed elsewhere.

XRF spectroscopy is most accurate when applied to finely crushed material. An open question is whether dust and cuttings collected directly from the borehole are suitable for XRF analysis as is, or whether they should be crushed further. For the results presented here, the samples collected in the field were crushed to powder with a small ball mill.

For future work, it is important to determine the relationship between grain size and XRF sensitivity/accuracy. One approach would be to collect a larger volume of dust in the cyclone that could be put through a sieve to retrieve only material with a very fine particle size. It might also be possible to sort particles directly during sample collection; inside the cyclone, large particles are separated first from the volume of material because they reach the cyclone's walls faster than smaller particles. However, this approach would introduce sampling errors depending on the degree to which particle size is related to elemental composition. Experiments and research would be required to determine the relationship between measured data and grain size.

Copper concentration in boreholes

Figure 5 shows the copper concentration measured in six boreholes located on the same bench. Individual samples were collected with the cyclone system continuously; the material collected for each sample corresponds to approximately 1.5-meters (5 ft) of borehole length. The samples were crushed to powder as described above, and analyzed with XRF spectroscopy to obtain copper concentrations. Copper concentrations can be measured reliably with a high level of accuracy (greater than 1 ppm). For the data displayed in Figure 5, the highest measured value of copper concentration is 3670 micrograms per gram; for the 90 samples collected and analyzed from the same bench, the highest concentration measured is 7110 microgram per gram. The borehole profiles shown in the figure indicate that the distribution of copper ore varies considerably over the length of the borehole, and between boreholes on the same bench. These results must be confirmed by analyzing the effect of sampling bias introduced by the collection method. This issue is discussed more fully in the following section.

Rock groups in boreholes

There is interest in determining if the XRF data can be used to help identify rock types or rock properties such as hardness that would be valuable information for blasting engineers. As a first step toward this goal, the XRF measurements described above were grouped using an empirical-classification scheme (statistical classification techniques are discussed in the following section).

To implement the classification scheme, the concentration data for each element are normalized by the maxi-

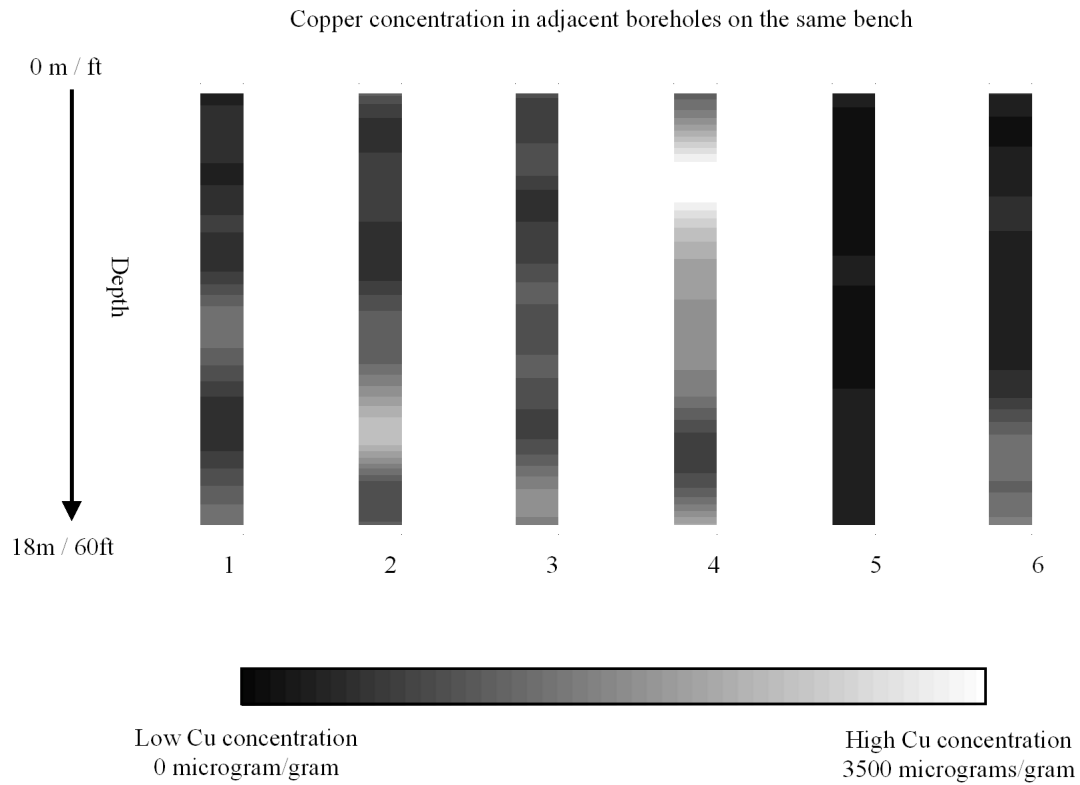


Figure 5. Borehole profiles of copper concentration measured in six boreholes located on the same bench. Samples were collected with the cyclone system during drilling (see Figure 4a); individual samples were collected approximately every 1.5 meters (5 ft). The samples collected were analyzed using XRF spectroscopy to obtain copper concentration.

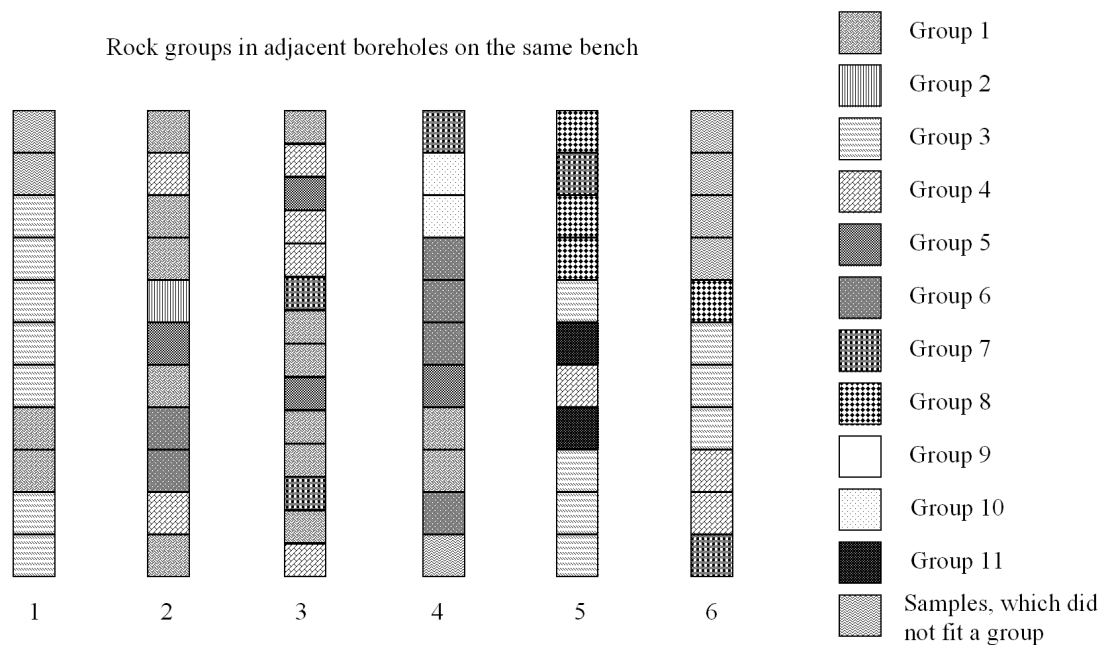


Figure 6. XRF measurements obtained for more than 90 samples collected during drilling were analyzed using an empirical-classification scheme to help determine if the data can be used to discern information about rock type and rock properties. The graph shows different rock groups identified in six boreholes; the copper content measured in the same boreholes is shown in Figure 5.

mum concentration measured for that element among all samples. For example, the highest copper concentration measured in the lot of 70 samples was 8360 micrograms per gram. All copper data are normalized by this value. Likewise, the highest concentration of zinc measured was 8470 micrograms per gram, and all measurements of zinc were normalized by this value. Each element measured in a sample is thus described as the percentage of the highest occurring concentration of that element among all samples. The first step in the classification scheme is based on pairwise comparisons of concentrations of elements common to both samples. The average of the absolute values of differences in concentration is the parameter that is used to determine if two samples belong in the same group. For example, if X_1 is the percentage of the first element in the first sample, and Y_1 is the percentage of the first element in the second sample, then the comparison C_1 is calculated as (equation 1):

$$C_1 = |X_1 - Y_1| \quad (1)$$

Such comparisons are made for all elements measured in both samples. Thus, there are n C values, where n is the number of elements that are present in both samples. The mean of the $C_1 \dots C_n$ values is calculated, and is the basis for identifying groups; i.e., the mean of the C values is compared to a "threshold" value that was determined based on analysis of data from known rock types. In addition, two rocks were crushed, and four nominally identical samples were taken for each rock. This made it possible to identify the variability in the XRF results for samples nominally the same.

For the 90 samples in the data set, it appears that the empirical method provides reasonable groupings when the threshold is on the order of five percent; i.e., samples with an average C value less than 0.05 are considered to be similar. The comparison is performed for all possible combinations of sample pairs. All the pairs identified as similar are then extracted to form a subset of data. The next step in the analysis is to build groups. Sample pairs with common members are identified as a group. For example, if the sample pairs $\{1,3\}$ and $\{2,3\}$ were identified as being similar, then the pair $\{1,2\}$ is considered similar as well. Samples $\{1,2,3\}$ are then grouped together. In this way, samples are included in the group that would not be identified from pairwise comparisons alone. There is no limitation on how many samples can be in one group. A group always contains at least two elements.

This method was applied to the 90 dust samples collected with the cyclone during drilling. Of these 90 samples, 85 returned a valid XRF spectroscopy measurement and 71 samples could be discerned into 11 groups. Figure 6 shows the distribution of groups in six boreholes, which were located on the same bench. Group 9 is not represented in any of the six boreholes shown, and Group 2

only appeared in a single borehole. As many as five individual groups were identified in a single borehole (borehole 5 in Figure 6). Some groups occurred at multiple depths in the same hole; for example, eight layers were identified in borehole 5 where five rock groups were identified. It is postulated that some of the samples, which were not placed in any of the groups may have been mixtures of two or more rock types. In work to date, the samples have not been analyzed by other assay techniques that would help determine if the groups identified correspond to identifiable rock types, which would indicate that the samples were grouped correctly. However, the 90 samples collected during drilling were compared to samples obtained from known rock types using the same classification method. No correlation could be established; however, the known samples are not from the same area of the mine as the 90 samples collected during drilling. Efforts are underway to expand the current database.

The method described in this section is empirical, and is based on normalized measurements of element concentrations. Any statistical analyses implemented in a production environment should be sample independent. New samples added to the current database could cause a change in the normalization procedure, and might affect the threshold value or even change the groupings. Nonetheless, the results to date are encouraging because they indicate that XRF analysis of samples collected during drilling might contain useful information about rock properties. Statistical analyses, such as those introduced in the following section, and more samples, are required to fully understand the relationships between element concentrations, mineralogy, and rock properties.

STATISTICAL ANALYSES

As discussed in the previous section, efforts are underway to determine if the XRF elemental-composition data can be used to identify rock type or rock properties, in addition to mineral content. Toward this goal, preliminary work has been undertaken applying descriptive data analysis and statistical clustering techniques to the XRF measurements from two sets of samples. The rock classification task is complicated by several factors including sampling errors, mixing of dust particles in the borehole, and the difficulty of trying to discern rock properties based on elemental composition. Sampling errors are introduced by the way in which the samples are obtained. At present, dust and cuttings are extracted from the borehole continuously, with each sample representing about 1.5 meters (5 ft) of borehole length. The samples are, thus, a mixture of the material in that length of borehole. It is also likely that the distribution of dust particles in the borehole depends in part on the mass and size of the particles. Thus, the dust collected at any point in time is likely to contain particles that come from rock at shallower depths. These sampling problems are, of course, also an issue for the mineral content measurements. This

section discusses these problems, and suggests some possible solutions.

For the results presented here, XRF analysis detected measurable concentrations of the following 18 elements: potassium, calcium, titanium, manganese, iron, nickel, copper, zinc, gallium, arsenic, selenium, bromine, rubidium, strontium, yttrium, zirconium, niobium, and lead. The statistical clustering technique described in the previous section, as well as a K-means technique, were applied to the Morenci samples to determine if rock groups could be identified from the XRF data. Clustering techniques do not require that each XRF measurement be from a known rock type, and provide some indication of how well statistical classification techniques (which do require the rock type of each sample to be known) will work (see M. I. Jordan and C. M. Bishop, 2001).

The basic K-means technique requires the number of rock groups to be identified and input to the clustering algorithm; the average elemental concentrations of each rock group, as well as the variance within each group, are returned as output. To obtain the number of rock groups required as input to apply the K-means algorithm, the clustering procedure outlined in the previous section was employed. Recall that the required input for that clustering procedure is a discernment threshold, which is a measure of “closeness” that indicates if two sets of XRF measurements are in the same rock group; the clustering procedure returns the number of rock groups as output. The “closeness threshold” used was chosen based on analysis applied to a set of known rock groups; this ensures that the technique provides reasonable groupings. The clustering procedure was applied to samples from unknown rock types with a threshold value of five percent; the resulting number of rock groups identified provides some indication of how many clusters to specify as input into the K-means algorithm. For the same number of clusters, K-means produced similar results, with the difference that all of the previously unassigned rock types were assigned to whatever cluster was “closest.”

As discussed above, a problem encountered in implementing statistical classification techniques is that the dust samples collected during drilling are often mixes of a variety of constituent rock types. The presence of mixing means that the measured concentrations are a weighted average of the elemental concentrations of the constituent rock types in the mix. For example, if the mix is of two rock types with elemental concentrations e_1 and e_2 , then the elemental concentration of the mix is (equation 2):

$$p e_1 + (1 - p) e_2 \quad (2)$$

where p is the proportion of rock type one in the mix. Such mixing introduces a bias into the means calculated using standard clustering methods that makes them appear

closer together than they are, and thus more difficult to discern. Consider the following example with simulated data, chosen for ease of illustration, with two rock types, each with components composed of two elements (such as, for example, SiO_2). The simulated elemental concentration data were generated randomly from two bivariate Gaussian distributions; one with mean concentrations of the two elements of 0.125 and 0.375, and the other with means of 0.375 and 0.125. A scatterplot of the simulated data is shown in Figure 7a. The K-means algorithm correctly discerns the two clusters and provides consistent estimates of their means. The conditional variance of each cluster is also a consistent estimate of the true cluster variance, so in this case we can also use statistical inference to discern the clusters (and determine whether the differences are likely to be due to chance).

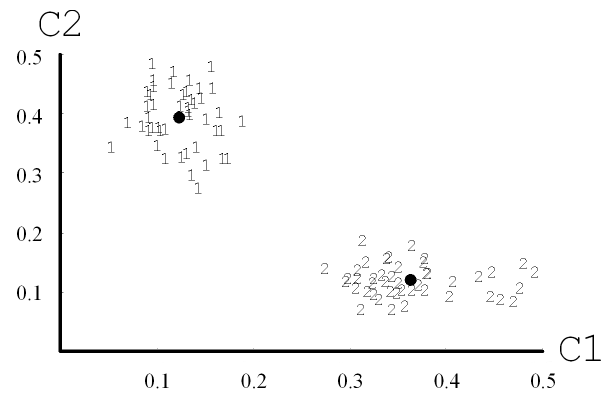


Figure 7A. Scatterplot of simulated mineral-concentration data generated randomly from two bivariate-Gaussian distributions. If it is assumed that there is no mixing between the two groups during sampling, then the K-means algorithm correctly discerns the two clusters and provides consistent estimates of their means.

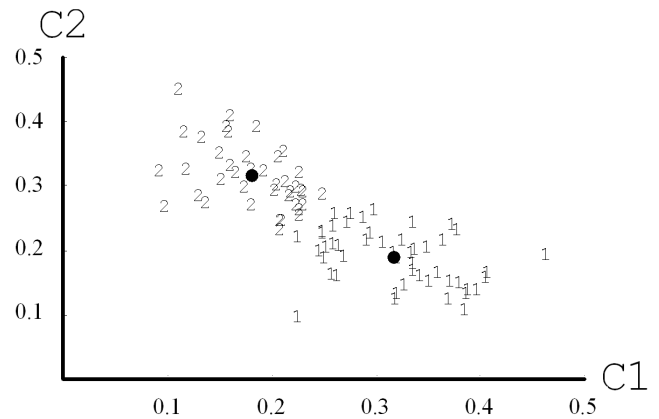


Figure 7b. Scatterplot of simulated mineral concentration data generated randomly from a mix of the same bivariate Gaussian distributions as the data plotted in Figure 7a. With mixing, the K-means algorithm still discerns two clusters, but the cluster means are biased estimates of the true underlying means for the two rock types.

Mixing in the borehole means that the concentration measured is a combination of the concentration of elements in the two rock types. Figure 7b shows a scatter plot of data generated from the same two bivariate Gaussian distributions as before, but with each data point a random mix of both, rather than being drawn purely from one distribution or the other. This requires that the mixing proportion p also be generated randomly (with all outcomes equally likely). Comparing Figures 7a and 7b shows how mixing blurs the distinction between the clusters. In the presence of mixing, the calculated cluster means are not consistent estimates of the means of the underlying component distributions; the calculated means are biased such that they are closer to one another than the true cluster means. However, with additional work, it may be possible to modify standard clustering techniques to discern the correct means of the component rock types, even in the presence of mixing. Meanwhile, the clustering results should be interpreted cautiously.

Because mixing blurs the distinction between rock groups it will also make statistical classification more difficult (note that statisticians often distinguish between classification and clustering techniques, although they are closely related). Even when mixing is not present, that XRF detects only certain minerals also complicates the task of classification. There is, however, additional information that is relevant for improving the classification accuracy. For example, for elements not detectable using XRF analysis, it may still be possible to say something about their elemental concentrations. In some rock types, elements may occur in proportion to other elements that are XRF detectable. An example from the samples analyzed to date is gallium, whose presence is strongly correlated to that of copper; the correlations between copper and trace elements measured are summarized in Table I. If correlations between elements that are and are not XRF detectable can be established for a particular site, they can be used to predict the presence of nondetectable elements from the XRF data (Figure 8).

Table I. Copper Correlation with Trace Elements in Dust Samples

	Copper
Gallium	0.86
Zinc	0.75
Manganese	0.69
Yttrium	0.65
Calcium	0.59
Nickel	0.52

For using XRF data to discern rock types or rock properties, site-specific information can also be used to improve the accuracy of classification techniques. For example, determining spatial correlations in the distribution of rock types would be useful for refining the XRF classification and improving the prediction of classification

algorithms. Further research is necessary to establish the spatial relationships and correlations between elements that might be useful for rock classification.

While XRF analysis promises to be a useful tool, it is not sufficient by itself to correctly classify all rock types. Nonetheless, a coarser classification might still provide useful information to geologists and mining engineers, and XRF data may still suffice for this purpose.

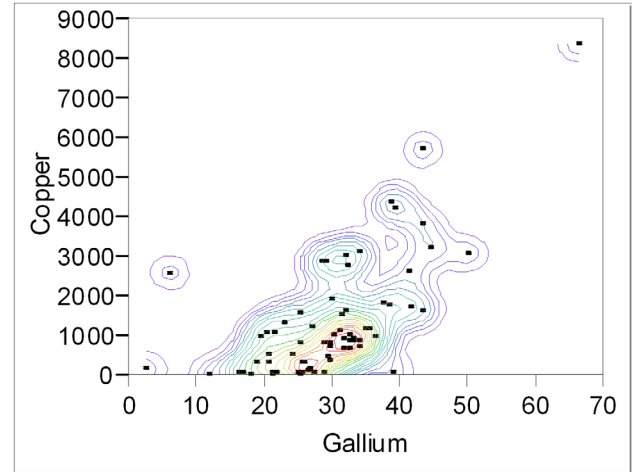


Figure 8. Kernel density contour plot showing the correlation between copper and gallium (ppm) in the data set with 70 samples.

CONCLUSIONS

Field tests conducted with a prototype sample collection system demonstrate that it is possible to continuously sample dust and cuttings during drilling. The system is robust, with no moving parts, and is easily mounted on a drill rig. A variety of samples collected in the field have been analyzed by XRF spectroscopy to measure mineral content. The data collected during drilling has been used to create borehole profiles of copper concentration. These results suggest that continuous online sampling and real-time XRF analysis of samples collected is a feasible alternative to laboratory assay of dust and cuttings obtained from boreholes post drilling. Such a system would provide much more detailed information than that currently available, with the potential to allow three-dimensional mineralogical maps to be created while drilling. An integrated sample collection and mineral-content analysis system could be built either as a stand-alone system, or integrated with existing software packages that collect and display other drill data. The technology for sampling dust/cuttings during drilling could be commercialized separately; in this scenario the samples would be analyzed off line, for example, in the mine's assay lab. An XRF analysis and display system could also be developed as a stand-alone system; in this case, a portable unit would be built for use by mining personnel to measure and analyze

mineral content in the field using existing sample collection techniques.

Work is also underway to determine if the XRF elemental composition data can be used to identify rock type or rock properties. Toward this goal, descriptive data analysis and statistical clustering techniques have been applied to the XRF measurements from two sets of samples. The clustering techniques allow different rock groups to be identified, but these results should be interpreted cautiously. The rock classification task is complicated by several factors, including sampling errors, mixing of dust particles in the borehole, and the difficulty of trying to discern rock properties based on elemental composition. It may be possible to modify standard clustering techniques to discern the means of the component rock types, even in the presence of mixing. Site-specific information can be used to improve the accuracy of classification techniques. Additional research is also necessary to establish correlations between elements that might be useful for rock classification.

In summary, work to date has demonstrated the feasibility of collecting samples while drilling and using XRF spectroscopy to analyze the mineral content of the samples collected. There are no technological barriers to automating sample collection or mineral analysis. A critical research and engineering challenge is designing a system that will ensure the ability to obtain representative samples. The data can be used to create three-dimensional mineralogical maps, and hold promise for improving processing efficiency by helping to ensure that material is routed to the appropriate processing stream, and providing information to engineers that can be used to help optimize blasting. XRF measurements alone are not sufficient to correctly classify all rock types. Nonetheless, a coarser classification might still provide information that is useful to geologists and mining engineers.

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